

Estimating Human Capital's Contribution to Economic Growth

- a comparative analysis



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January 2008

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Preface

First and foremost, I would like to thank my supervisor Mads Greaker at Statistics Norway for indispensable guidance, interesting discussions, and general encouragement. Also thanks to Ragnar Nymoen, Professor of Economics at the University of Oslo, for helpful feedback on the econometric part of this thesis. I would also like to thank Rafael Doménech, Deputy Director of the Economic Bureau of the Prime Minister of Spain and co-author of articles important to this thesis, for supplying data and taking the time to answer questions.

Oslo, January 2008

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1 Summary

This thesis investigates the causes of the contradictory conclusions of Pritchett (1996) and De la Fuente & Doménech (2002 and 2006) on the role played by growth in human capital in explaining growth in output. While both models are based on a variation of an augmented Solow model, much in accordance with Mankiw, Romer & Weil (1992), Pritchett finds that cross-national data show no association between growth in human capital, measured by growth in educational attainment, and growth in output. Opposite to this finding, De la Fuente & Doménech's results propose a coefficient for human capital growth of well above 0.50, and suggests that schooling data of poor quality is a likely source to the discouraging results on the contribution of human capital, found by Pritchett and also other researchers. This thesis examines the differences in the educational datasets composed by Barro & Lee (1993), used by Pritchett, and De la Fuente & Doménech (2002) for 21 OECD countries using five-year growth periods from 1960 to 1985, and finds that there are large disparities in both levels and growth rates between the datasets. Barro & Lee's data is found to contain implausible jumps and breaks, and over 14% of the growth rates are reported to be negative. This seems highly questionable. De la Fuente & Doménech's dataset projects much smoother growth in educational attainment, and reports no periods of negative growth. However, these large differences in human capital data are not sufficient to explain the contradicting results. Through regressions on several different variations of both models, other important factors contributing to the disparities are identified:

- Differences in the datasets on output per worker
- Differences in the datasets on physical capital per worker
- Excluding/including time fixed effects in the model
- The calculation method for the proxy on human capital

It is through the cumulative effect of all these dissimilarities that the opposing views on human capital are based. The estimated coefficients on growth in human capital are also found to be highly sensitive to seemingly small alterations in the model or any of its inputs. This suggests that further research and larger data samples are needed before any conclusions on the impact of human capital should be made.

All econometrical calculations and estimates in this paper are produced using the panel data package within PcGive 10.0 - GiveWin 2.20 or using Microsoft Excel.

2 Introduction

Throughout modern history, economists have been fascinated with what causes differences in economic wealth. In 2000, GDP per capita in the United States was \$33330 (in 1996 \$ prices), reflecting a high standard of living when compared to many other countries; approximately \$9000 in Mexico, \$4000 in China, \$2500 in India and only \$1000 in Nigeria. Why are some countries rich and some countries poor, and how can poor countries catch up?

The only conceivable way of accomplishing substantial increases in a countries output is through high growth rates sustained over long periods of time. Small differences in growth rates can lead to vast differences over time. Consider the case of the US: In 1870 (in 1996 \$ prices), real per capita GDP was \$3340. Since then the average annual growth of GDP per capita was 1.8%. If growth instead had been 0.8%, close to the rate of India (0.64%), Pakistan (0.88%) and the Philippines (0.86%), GDP per capita in 2000 would be \$9450, close to that of Mexico, and ranked 45th out of 150 countries with data instead of 2nd. If the average growth had instead been 2.8%, close to that of Japan (2.95% from 1890-1990) and Taiwan (2.75% from 1900-1987), capital per GDP in 2000 would instead have been \$127000.¹ Economic growth matters!

One of the factors often mentioned as inducing economic growth, is education. Governments all over the world can be seen encouraging increased education through providing benefits such as student loans, cheaper accommodation, public transportation and various other student discounts. Also development aid focuses on education. This also seems reasonable seen from a general economic perspective; education increases the skill level, which increases productivity, and higher levels of productivity leads to higher output and a higher standard of living. In accordance with this intuitive reasoning, many economists have incorporated human capital as an explanatory variable in their growth models, i.e. Romer (1990) and Mankiw, Romer & Weil (1992), finding that human capital does matter when explaining differences in output between countries. However, in contrast to these findings, several research articles on the effects of increased education have produced very dubious results. Some even find that education seems to have no, or possibly even negative impact on economic growth. One

¹ Numbers from Barro & Sala-i-Martin (2003)

example of such an article is written by Lant Pritchett (1996), who finds that cross-national data show no association between increases in human capital (attributable to growth in educational attainment of the labour force), and the growth of output per worker. In fact, for the majority of his specifications, the coefficient for growth in human capital enters with a negative sign! In stark contrast to these findings De la Fuente & Doménech (2002) state that by increasing the quality of the schooling data, educational attainment enters positively and significantly when trying to explain growth in output. This paper investigates the two abovementioned articles in detail, and tries to shed some light on how these opposing views on the economic importance of human capital have evolved. This thesis analyzes the different approaches used by the respective authors and tries to answer the following:

- How much of the differences can be traced back to the underlying datasets on schooling?
- How much is caused by the construction of the models themselves?
- Are there other factors that may be influencing the results, i.e. data used for physical capital and output?

The layout of the thesis is as follows: Chapter 3 gives a brief review of the theoretical background that Pritchett (1996) and De la Fuente & Doménech (2002) base their papers on, followed by a brief review of the findings of these articles. Chapter 4 examines the datasets on educational attainment used as basis to create a proxy for growth in human capital in abovementioned articles. In chapter 5, the two models are investigated in detail. Chapter 6 shows the results of regressing Pritchett's and De la Fuente & Doménech's models using different data as basis for dependent as well as explanatory variables. Finally, the thesis concludes with chapter 7, where the results are investigated, and the causes for the disagreement in the results of the two articles are identified.

3 Theoretical framework and literature review

Educational attainment has, throughout modern economic history, served as the major source of information on cross-sectional differences in human capital. However, it is important to recognize that the term human capital, if considered broadly, is intended to include such important variables as “*knowledge, health, skills and abilities*” – as defined by the newly formed Journal of Human Capital (2007). Educational attainment therefore serves, at best, as a proxy for human capital.

This chapter is by no means intended to be a complete historical survey of human capital in economic growth theory. However, it seeks to shed some light on the evolvement of, and motivation for, the models relevant to this paper. Furthermore, it investigates how such vast differences in the view upon the role human capital plays for economic growth, have emerged even within what is basically the same economic model! Focus will be on the sections of the papers/articles most significant to this thesis, and its major focus point; the relevance of quality data on education.

The chapter starts with a brief explanation of the classic Solow model, followed by a review of arguably the most seminal article on the subject of human capital in growth-economics; “*A contribution to the Empirics of Economic Growth*” written by Mankiw, Romer and Weil (1992). This article serves as a natural point of origin for our further discussion, as the models that are important for this paper have fundamental similarities with the model set forward in this article. In fact, Pritchett (1996), which much of this paper is based upon, is mostly a critique of MRW’s model and its findings. Pritchett is not alone in scrutinizing the article, over the years it has become widely discussed, and has, at least in parts, influenced much of the recent research within the field.² Some of the most well-known articles criticizing MRW’s article are also briefly mentioned in this chapter. Other well known growth models that include human capital i.e. Lucas (1988) and Romer (1990) are not discussed, as they are considered beyond the scope of this paper.

The chapter is concluded with a brief summary of the results set forward in Pritchett (1996) and in de la Fuente & Doménech (2002). These articles will be dealt with more mathematically and in further detail in chapter 5.

² See i.e. Benhabib and Spiegel (1994) and Klenow and Rodríguez-Clare (1997), both of whom will be commented on later in this thesis.

3.1 The Solow model

In the following notation commonly used in current teaching of the Solow model is used, as this fits very well with the notation in the next subchapter (MRW). This is not at odds with Solow (1956 and 1957), and makes the transition to the Augmented Solow model in the next subchapter somewhat easier to follow.

The Solow model (1956 and 1957), named after Robert M. Solow (awarded the Nobel-prize of economics in 1987), simplifies the aggregate production function so that growth in aggregate output (Y) is explained by growth in inputs capital (K) and labour (L). What is not explained by these two inputs is attributed to “technical change” and treated as a shift in the production function.

Labour is assumed homogenous, and the growth rate of the labour force (n) is assumed exogenously given:

$$(3.1) \quad \dot{L}/L = n$$

Growth in capital comes from investment, which equals savings as we are looking at a closed economy with no government sector (output, Y , can either be consumed or saved/invested to create more capital). Thus the evolution of the capital stock is

$$(3.2) \quad \dot{K}(t) = S(t) - \delta K(t)$$

where δ = depreciation rate of capital, and $S(t)$ = savings

Assuming a Cobb Douglas aggregate production function:

$$(3.3) \quad Y(t) = F[K(t), L(t)] = K(t)^\alpha L(t)^{1-\alpha} \quad 0 < \alpha < 1$$

and neoclassical properties;

- Positive and diminishing marginal products
- Constant returns to scale (CRS)
- Inada conditions satisfied

Writing the production function on intensive (per worker) form, where output per worker (y) is a function of capital $f(k)$:

$$(3.4) \quad y = f(k)$$

Inserting for a fixed savings rate $S(t) = sY(t)$ and using the characteristics of equation (3.4), equation (3.2) becomes $\dot{K} / L = sf(k) - \delta k$, and given that $\dot{k} = \dot{K} / L - nk$ the fundamental equation of the basic Solow model is stated as:

$$(3.5) \quad \dot{k} = sf(k) - (n + \delta)k$$

From (3.5) it can be seen that when investments in capital exceeds depreciation of capital ($sf(k) > (n + \delta)k$), the capital stock increases. When investments fall short of depreciation, ($sf(k) < (n + \delta)k$) the capital stock shrinks, and when investments are equal to depreciation ($sf(k) = (n + \delta)k$) the capital stock stays constant (remember that notations are in per worker terms). In this model, countries converge towards their own steady states, where $\dot{k} = 0$, determined by their exogenously given savings rates, growth in labour force, and the depreciation rate. It is important to note that this situation is fundamentally dependent on the assumption of diminishing returns to capital.³

In a steady state, no growth in output per capita is due to increased capital (Y , K and L , the aggregate amounts, grow at the same rate $= n$), and if no exogenous shocks, growth in output per capita will therefore be equal to zero. Higher saving rates can produce temporary increases in the growth rate of output, through temporary higher growth in capital per capita, but due to diminishing returns to capital, it cannot get the economy to a path involving a faster steady-state growth rate.

So how can long-run growth above the exogenously given growth in the workforce (n) occur? Well, so far the model has not included technological progress and development.

³ If we had constant returns to capital and i.e. $sf(k) > (n + \delta)k$ we could have a situation of perpetual growth in capital per worker. It is however reasonable that as capital (i.e. machines per person) increases, the marginal returns to introducing the first unit of physical capital is higher than the second and so forth. Hence the assumption of diminishing returns to capital seems credible.

Solow uses the phrase “technical change” for any kind of shift in the production function. Such shifts may stem from slowdowns, speed-ups, improvements in education and all other sorts of things. Hence, Solow treats both technological and human capital changes, as well as other “exogenous shocks” as shifts affecting the productive efficiency. Since increases in this productive efficiency will increase productivity of the other factors, it has come to be known as total factor productivity (TFP). Expanding equation (3.3) to include TFP results in:

$$(3.6) \quad Y(t) = K(t)^\alpha (A(t)L(t))^{1-\alpha} \quad 0 < \alpha < 1$$

Where $A(t)$ is a multiplicative factor that measures the cumulated effect of abovementioned shifts over time, and is assumed to grow with the exogenously given rate g so that

$$(3.7) \quad A(t) = A(0)e^{gt}$$

The number of effective units of labour, $A(t)L(t)$, grows at rate $n + g$. Redefining k as the capital stock per effective unit of labour $k = K / AL$ and y as output per effective unit of labour, $y = Y / AL$. The fundamental equation corresponding to equation (3.5) above, now takes the form

$$(3.8) \quad \dot{k}(t) = sf(k) - (n + g + \delta)k(t)$$

or more specifically

$$(3.9) \quad \dot{k}(t) = sk(t)^\alpha - (n + g + \delta)k(t)$$

So k converges to a steady state amount of capital per effective unit of labour denoted k^* , where $\dot{k}(t) = 0$ and k^* therefore is defined by $sk^{*\alpha} = (n + g + \delta)k^*$ and solving for k^* yields:

$$(3.10) \quad k^* = [s / (n + g + \delta)]^{1/(1-\alpha)}$$

Substituting equation (3.7) and (3.10) into the production function (3.6) and taking logs, steady-state income per capita (in logs) is:

$$(3.11) \quad \ln \left[\frac{Y(t)}{L(t)} \right] = \ln A(0) + gt + \frac{\alpha}{1-\alpha} \ln(s) - \frac{\alpha}{1-\alpha} \ln(n + g + \delta)$$

Equation (3.11) states that output per capita at time t is explained by an initial level of technology, growth in technology since the initial level, steady state savings rate and steady state levels of the term $(n + g + \delta)$. And since it is common to assume that capital's share of income (α) is approximately $1/3$, the Solow model also predicts the respective coefficients: 0.5 with respect to the savings rate, and -0.5 with respect to $(n + g + \delta)$.

In Solow (1957) the theoretical framework was used to try to explain growth in the U.S. economy in the period 1909-1949, with output per unit of labour as the dependent variable, capital per unit of labour and the share of capital as inputs. The growth in output per capita that cannot be accounted for by increases in capital is attributed to “technical change”. This has later been commonly referred to as the “Solow residual”. Solow applies these variables to perform an econometric specification known as growth accounting, where he concluded that output per man roughly doubled over the period, with 12.5% explained by increased use of capital and 87.5% attributable to “technical change”.

3.2 Mankiw, Romer & Weil – The Augmented Solow-model

In Mankiw, Romer and Weil (1992, henceforth MRW), the authors, Gregory Mankiw, David Romer and David Weil, introduce human capital as an explanatory variable, thus expanding the Solow-model. The introduction of human capital caused renewed interest in neoclassical growth models⁴, and thus triggered a neoclassical revival. The new model was named the Augmented-Solow-model.

⁴ The neoclassical growth model is a macro model in which the long-run growth rate of output per worker is determined by an exogenous rate of technological progress, like those following from Ramsey (1928), Solow (1956), Cass (1965), and Koopmans (1965).

The aggregate production function now takes the form;

$$(3.12) \quad Y(t) = K(t)^\alpha H(t)^\beta (A(t)L(t))^{1-\alpha-\beta}$$

where $A(t)$ - Total factor productivity/ the Solow residual, still is treated as exogenous.

Growth of physical capital per capita is shown below:

$$(3.13) \quad \dot{k}(t) = s_k y(t) - (n + g + \delta)k(t)$$

Where s_k is the exogenously given fraction of income invested in physical capital. While growth of human capital is accounted for in a similar way:

$$(3.14) \quad \dot{h}(t) = s_h y(t) - (n + g + \delta)h(t)$$

s_h is the fraction of income invested in human capital, and as in the basic Solow model, both physical and human capital move towards their steady state values, as the model assumes diminishing returns to total capital ($\alpha + \beta < 1$).⁵ The steady state values, where $\dot{k}(t)$ and $\dot{h}(t)$ are equal to zero, are:

$$(3.15) \quad k^* = \left(\frac{s_k^{1-\beta} s_h^\beta}{n + g + \delta} \right)^{1/(1-\alpha-\beta)}$$

$$(3.16) \quad h^* = \left(\frac{s_k^\alpha s_h^{1-\alpha}}{n + g + \delta} \right)^{1/(1-\alpha-\beta)}$$

and substituting these into the production function and taking logs:

⁵ Equations (3.13) and (3.14) are basically the same as equation (3.9) in the case of the Solow model. But since we are now dealing with a system with two dynamic equations, the details of the steady state solutions found by inserting $y(t) = f(k, h) = k^\alpha h^\beta$ into equation (3.13) and (3.14) and solving, becomes somewhat more complicated. The math of this solution is not essential to this paper, and is therefore not dealt with in further detail.

$$(3.17) \quad \ln \left[\frac{Y(t)}{L(t)} \right] = \ln A(0) + gt - \frac{\alpha + \beta}{1 - \alpha - \beta} \ln(n + g + \delta) + \frac{\alpha}{1 - \alpha - \beta} \ln(s_k) + \frac{\beta}{1 - \alpha - \beta} \ln(s_h)$$

As before physical capitals share of income (α) is assumed 1/3, and MRW argue for a human capital share of income (β) of between 1/3 and 1/2. They arrive at such numbers by arguing that in USA the minimum wage (assumed to be the return to labour with no human capital) has averaged 30-50% of the average wage in manufacturing. This suggests that 50-70 % of total labour income stems from human capital. This implies a (β) as stated above.

As a proxy for the rate of human capital accumulation, which is assumed to be the amount of savings invested in human capital, (s_h), MRW focused on investment in human capital in the form of education, ignoring among others, investment in health and on the job training. The measurement of human capital was further concentrated to measure the percentage of the working-age population in secondary school. Based on data on the fraction of the eligible population (defined as youth aged 12 to 17) enrolled in secondary school from the UNESCO yearbook. This is then multiplied with the fraction of the working-aged population that is of school age (15 to 19). From MRW (1992, page 419):

This variable, which we call SCHOOL, is clearly imperfect: the age ranges in the two data series are not exactly the same, the variable does not include the input of teachers, and it completely ignores primary and higher education.

As stated in this quotation, MRW acknowledge the shortcomings of their approximation of educational attainment, but they argue that the model is a better fit than a pure Solow-model, where output per capita, as seen earlier, is explained only by physical capital per capita, the rest being attributed to “technical change”. MRW applies their model by regressing with the log of GDP per working-age person in 1985, as the dependent variable, and the log of the investment rate ($\ln(I/GDP)$), the log of $\ln(n + g + \delta)$ and the log of the percentage of the population in secondary school, ($\ln(SCHOOL)$), as explanatory variables. They find that the human capital measure enters significantly in all three samples they focus on. The results they get are also “in favour of” the inclusion of human capital: *“These three variables explain*

almost 80 percent of the cross-country variation in income per capita in the non-oil and intermediate samples” MRW (1992, page 421). With such a “crude” model, these results are indeed very good. By including human capital as an explanatory variable, \bar{R}^2 increases from 0.59 (in the pure Solow model) to 0.78 for the non-oil sample (98 countries), and from 0.59 to 0.77 for the intermediate sample (75 countries). However, in the case of OECD (22 countries), \bar{R}^2 remains quite low, but still increases from 0.01 to 0.24.

3.3 Critique of the Augmented Solow model

The paper by Mankiw, Romer and Weil (1992) has received a lot of attention in economic circles, and has also been the target of much critique. Especially the authors’ use of only secondary school enrolment as proxy for human capital has been scrutinized.

Benhabib and Spiegel (1994)

In chapter 2 of Benhabib and Spiegel (1994) a standard Cobb Douglas production function is used to create an augmented Solow model identical to the one discussed in the preceding subchapter. They find that human capital growth enters insignificantly and usually with a negative sign when trying to explain growth in per capita output. This result is found to be robust to a number of different specifications and data sources (average years of schooling from Kyriacou (1991), average years of schooling from Barro & Lee (1993), and also using literacy-levels), and also for the possibility of bias encountered from regressing per capita income growth on accumulated factors of production.

Klenow and Rodríguez-Clare (1997)

In Klenow and Rodríguez-Clare (1997), chapter 2, the authors Peter J. Klenow and Andrés Rodríguez-Clare, show how sensitive MRW’s findings are to modifications in how human capital is measured. By replicating their findings, and then extending the data used for human capital to include all levels of schooling (by including primary and tertiary enrolment instead of only secondary using data from Barro & Lee (1993)), they find that \bar{R}^2 (r-squared adjusted) is reduced from 0.78 to 0.40. Implying that only 40% of a units increase in output is explained by increased physical and human capital combined (they choose not to distinguish between the two different capitals in this part of their paper), and as much as 60% is thus explained by the residual; total factor productivity. This must be considered a very large change, when considering the modest and highly justifiable alteration in proxy for human capital. Klenow

and Rodríguez-Clare also conclude that primary enrolment rates vary much less than secondary, and leaving them out therefore exaggerates the variation in the proxy for human capital. They further argue against MRW's assumption of the same technology for producing physical and human capital, and state that the production of human capital is more labour intensive than physical capital.

3.4 Pritchett (1996)

Lant Pritchett seeks to investigate the impact of human capital on economic growth. Unlike Mankiw, Romer & Weil (1992) who focuses on levels in one single year (1985), Pritchett focuses on how growth in GDP per worker in the period 1960 to 1985 is explained by growth in human and physical capital. The intuitive linkage between the two approaches is that if the level of human capital can significantly contribute to explain cross country differences in output per worker in 1985, it seems rational that growth in human capital should also have contributed to growth of output in the period 1960-1985, where the educational attainment levels increased at a historically unprecedented pace. Another difference between the two papers is that Pritchett does not assume that the different countries (necessarily) are at their steady states with respect to physical and human capital per worker. To construct a proxy for human capital, Pritchett focuses on average years of schooling from the datasets of Barro and Lee (1993) and Nehru, Swanson and Dubey (1995). Pritchett also investigates the importance of the growth accounting residual (earlier mentioned as the Solow residual and Total Factor Productivity (TFP)). Chapter 5.1 takes a closer look at the construction of Pritchett's model but for now let's review the findings of his research.

The results of the cross-national econometric estimation for the period 1960-1985 yielded some very strange results regarding the impact of growth in human capital (measured by growth in educational attainment), on growth of per worker GDP. For the entire sample (91 countries), the regression stipulates a negative (-0.049) and insignificant ($t=1.07$) impact, implying that there is no positive effect on output per worker of additional education! These findings hold true for both underlying datasets, and for several different specifications. He also finds that educational capital accumulation is strongly statistically significant and *negatively* related to TFP growth. These results question the whole basis for the Augmented Solow-model, and also contradict a priori thoughts on the matter. It is after all generally assumed that increased education, on average, makes a positive contribution to economic

growth and prosperity. Pritchett, it seems, is not convinced of this, and he suggests several possible reasons why education may have no, or even negative, effects on GDP per worker:

- Marginal returns to education could have fallen rapidly as the supply of educated labour expanded while demand remained stagnant.
- Educational quality could have been so low that years of schooling created no human capital.
- The institutional/governance environment could have been sufficiently perverse so that accumulation of educational capital lowered economic growth.

This third possible cause for the shortcomings of educational growth's impact might need to be clarified somewhat; Education raises the productivity of the population, and there is sufficient demand for educated personnel, but there exists possibilities for the educated that are personally attractive, but socially counterproductive. An example Pritchett uses is that of piracy, originally set forward by Douglass North (1990):

To be a successful pirate one needs to know a great deal about naval warfare, the trade routes of commercial shipping; the armament, rigging, and crew size of potential victims; and the market for booty.

The thought is that if the increased knowledge from education can be used in for instance illegal activities, and the risks of being penalized are sufficiently low, one might find that education lowers economic growth also at the aggregate level. Many countries suffer from high levels of corruption, especially within politics and bureaucratic institutions, which usually are run by highly educated personnel. However, not everybody is convinced by Pritchett's arguments.

3.5 De la Fuente and Doménech (2002)

Angel de la Fuente & Rafael Doménech (henceforth D&D) have co-written several articles where educational attainment and growth has been the topic, and much of their research relevant to this paper can be found in their paper "*Human capital in growth regressions: how much difference does data quality make? An update and further results*" (2002). It suggests

that instead of discarding the Augmented Solow model, one should instead look at other reasons for the mismatch between the idea of education contributing to economic growth, and the results in the papers discussed above; their prime suspect being poor data quality. The first part of the paper reviews some of the most utilized schooling datasets in empirical growth literature. They document suspicious features and also inconsistencies that suggest that these datasets contain substantial measurement error. They therefore construct a revised version of (a subset of) Barro and Lee's (1993) data set, consisting of 21 OECD countries, by using "previously unexploited sources". Following the procedure of Krueger and Lindahl (2001), D&D test their constructed data series using estimates of reliability ratios, and find that their series has the highest information content when considering the OECD-sample. In the second part of the paper, the performance of D&D's schooling series is compared with those of abovementioned datasets in a "number of standard growth specifications" with a constant returns to scale Cobb-Douglas aggregate production function as their base model. D&D find that there is a clear positive correlation between the quality of the dataset used, and the size and significance of the coefficient of human capital in growth regressions, and conclude that after correcting for measurement error bias, the value of this parameter is well above 0.50.

4 Educational datasets

This chapter takes a look at different datasets on educational attainment used in research articles on education (as a proxy for human capital) and its importance for economic growth. The focus is on the datasets constructed by Barro & Lee (1991) and De la Fuente & Doménech (2002), as these are used in the two research articles that are focused upon in this paper. Other often used datasets on schooling are only briefly mentioned and are collected in subchapter 4.3.

4.1 Barro & Lee (1993)

The authors Robert J. Barro and Jong-Wha Lee (B&L) construct a dataset on educational attainment consisting of 129 countries over five-year periods from 1960 to 1985. They choose, as a consequence of the available data, to focus upon educational attainment for the population over 25. 40% of the data consist of census and survey figures, while the rest is estimated by a perpetual inventory method. B&L have since this, revised their datasets several times, i.e. Barro & Lee (2000). However, as this paper focuses upon the differences between the datasets from D&D (2002) and B&L (1993), these later versions of Barro & Lee dataset are not addressed.

B&L divide the data into four different levels; no, primary, secondary, and higher schooling, and further differentiate between incomplete and complete attainment (for the three levels of schooling), thus leading to seven different levels. They also look at differences between the genders. The main sources for the survey and census information is UNESCO Statistical Yearbooks, Kaneko (1986), U.N. Demographic Yearbooks, and also some other sources. Ideally they would have been able to observe a total of 774 observations (129 countries*6 time series) for each of the mentioned levels. However, the information available gave only data for 40%, and only for the four major levels. To help fill in some of the gaps, they used adult illiteracy to proxy for non schooling in countries where this was possible. Most of the remaining cells are constructed by means of an estimation method that uses available data on school enrolment and the age of the population. With the census figures used as benchmark stocks (when available), school enrolment ratios are used to estimate changes from the

benchmarks. However, when assessing these constructed data, the authors conclude that this fill-in procedure was unsatisfactory for at least fractions of the sample, and choose to omit parts of it. The final data set therefore consists of full time series for only 106 of the 129 countries. The authors acknowledge that there may be substantial measurement errors also for the constructed figures that are incorporated in the data set.

B&L now turn to the task of dividing the data for the three major levels of schooling (primary, secondary and higher) into subcategories of whether or not the level is completed, when these statistics aren't available. Let us consider the case of primary school where they have at least one observation for the breakdown into complete/incomplete attainment for a total of 94 countries. From this data they construct the completion ratio for primary school (the fraction of the population above 25 that completed primary but did not enter secondary, divided by total primary that did not enter secondary). They assume that the ratio is determined by time-persistent country-specific features and features of the region (to which the country belongs to). From one single observation they in this way can create ratios for all six yearly observations. If no single observation was observable, they used the regional means. The same method is used when deriving completion ratios for secondary schooling, while for higher education they use the very limited data from Kaneko (1986), which reports the share of tertiary students with and without degrees for a total of 37 countries from U.N. surveys undertaken from 1975-1984. So for those countries where at least one observation is observable, B&L assume no variations in the ratio over time. For the remaining countries, they use the average completion ratio of the region. After creating their measures on completion ratios for the different schooling levels, average years of schooling is then calculated in the following way:

$$(4.1) \quad = DUR_p * [\frac{1}{2} h_{ip} + h_{cp}] + (DUR_p + DUR_{s1}) * h_{is} + (DUR_p + DUR_{s1} + DUR_{s2}) * h_{cs} + \\ [DUR_p + DUR_{s1} + DUR_{s2} + \frac{1}{2} DUR_h] * h_{ih} + (DUR_p + DUR_{s1} + DUR_{s2} + DUR_h) * h_{ch}$$

Where they multiply the duration of the different sub-levels of educational attainment, DUR_i = duration in years of the i th level of schooling⁶, with the fraction of the population with this

⁶ $i=ip$ for incomplete primary, p for primary, $s1$ for first cycle of secondary, $s2$ for second cycle of secondary, ih for incomplete higher, and h for completed higher education.

level of attainment as their highest attained (h). They assign half of the duration of primary school to the fraction of the adult population who entered but did not complete this level, and half of the duration of higher education to the fraction that entered higher education but did not complete this level. They also take account of differences in the years of schooling at each level, which differs across countries (data on duration from UNESCO's statistical yearbook in 1965), but neglect possible variations in this over time.

4.2 De la Fuente & Doménech (2002)

After concluding that the schooling datasets available suffer from a large amount of noise that can be traced back to inconsistencies in the underlying statistics, De La Fuente and Doménech seek to construct a modified version of their previously published dataset (De la Fuente & Doménech (2000)) for 21 OECD countries for the period 1960-1995. This series is essentially a revised version of (a subset of) Barro and Lee's (1993) dataset, which they in D&D (2000) argue is the best available source on human capital stocks. Their goal is to improve this dataset further, by utilizing a greater amount of national information, and they also seek to eradicate implausible breaks in the data, by correcting for what they identify as changes in the underlying classification criteria. D&D validate their focus on the OECD partly due to data availability and partly because the OECD sample is the one that Mankiw, Romer and Weil (1992) found weakest support for. In this latest revision, D&D also make use of a fair amount of new information supplied by the national statistic offices of about a dozen countries. They also extend the series to 1995 for about three fourths of the sample. They provide estimates of the fraction of the population age 25 and over, in each of the following subgroups; illiterates, primary schooling, lower and upper secondary schooling, and two levels of higher education. Illiterates are only reported for four countries (Portugal, Greece, Spain and Italy) where they enter in significant numbers in the sample period. Information on educational attainment is collected from both international publications and national sources (census and surveys, national yearbooks and unpublished national and OECD data), and this is used to create plausible attainment profiles for each country. Missing observations are filled in a variety of ways: When possible, D&D interpolate between observed levels. If this is not possible, backward or forward projections based on educational attainment by age group is used. They also use neighbouring countries, with similar educational systems, to divide between different sublevels of schooling. D&D choose to avoid using flow estimates based on enrolment data as they seem to produce implausible time profiles. They acknowledge that their estimates

includes a fair amount of guesswork, and relies more on judgement than taking it for granted that the primary data is of good quality. Using these schooling series, they construct an estimate of average years of schooling.

4.3 Other datasets

Psacharopoulos and Arriagada (1986)

Psacharopoulos and Arriagada (1986), use census and survey data to compile information about the educational attainment of the labour force (or, in some cases, of the adult population). Their dataset is however very small: most countries have only one time-series observation, and the year covered differs across the countries.

Kyriacou (1991)

Kyriacou (1991) constructs panel estimates of educational attainment for 111 countries. He relates the available census figures from Psacharopoulos and Arriagada (1986) for years in the 1970s, to school enrolment ratios from UNESCO. He then extrapolates this relationship to other years by using the data on school enrolment ratios, by a simple regression of educational stocks on lagged flows to estimate the unavailable levels of schooling. His final dataset covers the period 1965-1985.

Lau, Jamison and Louat (1991) and Lau, Bhalla and Louat (1991):

Lau, Jamison and Louat (1991) and Lau, Bhalla and Louat (1991) provide panel estimates of educational attainment through using a perpetual inventory method where they cumulate flows of schooling, based on the school enrolment data and on assumptions about survival rates of the population. They do not use census benchmarks for starting or intermediate values of educational stocks which are consequently constructed purely based on backward extrapolation. The data is not corrected for dropouts, and thus students who start a certain level are thought to also finish that given level.

Nehru, Swanson and Dubey (1995)

Nehru, Swanson and Dubey's (1995) dataset is built from enrolment data, using a perpetual inventory method, and is then adjusted for mortality. The estimates are further corrected for grade repetition among students and country specific dropout rates for primary and secondary

students. Enrolment data as far back as 1930 is used for most countries, and as a consequence of this, they need not rely as much on backward extrapolation as i.e. Lau, Jamison and Louat (1991).

5 The models

In this chapter the models used in Pritchett (1996) (paper discussed in subchapter 3.4), and De la Fuente & Doménech (2002) (paper discussed in subchapter 3.5) are derived and explained. As the main objective of this thesis is to evaluate in what magnitude the different datasets on educational attainment contribute to the substantially differing results, it seems important to discuss the choices the respective authors have made. Even though the authors test their models in different settings and also vary the construction of the models quite a bit, the focus of this paper is on the equations that deal with growth in the respective variables, and how these equations are constructed. This focus is chosen since these equations have very similar specifications, while at the same time yielding very different results. They are also adequately described in the articles. Although the two articles, and their respective models, are based on the augmented Solow model (subchapter 3.2), there are made numerous different choices, assumptions and simplifications, that potentially may distort the results from focusing on the impact caused by using different schooling data. These differences will be investigated in detail in this chapter, as the equations that will be used in the econometric work of this thesis are derived. The econometric procedure is also outlined in this chapter.

5.1 Deriving the regression model of Pritchett (1996)

For more on the article as a whole and its conclusions, see subchapter 3.4.

Notation used by Pritchett:

N	Average years of schooling (for population age 25 and older)
r	Wage increment to one more year of schooling
\hat{y}	Growth rate of output per worker – (real GDP per worker)
\hat{a}	Growth rate of the growth-accounting residual (Total Factor Productivity)
α_k	Estimation coefficient for physical capital
\hat{k}	Growth of physical capital per worker (Cumulated Depreciated Investment Effort)
α_h	Estimation coefficient for human (educational) capital
\hat{h}	Growth of human (educational) capital per worker
w_N	Wage with N years of schooling
w_0	Wage with zero schooling – assumed equal to minimum wage
δ	Depreciation rate

$$(5.1) \quad \hat{y} = \hat{a} + \alpha_k * \hat{k} + \alpha_h * \hat{h}$$

Equation (5.1) is the main equation that Pritchett bases his various regressions upon. In it, growth in real gross domestic product per worker (\hat{y}), is explained by growth in “total factor productivity” per worker (\hat{a}), physical capital per worker (\hat{k}) and human capital per worker (\hat{h}). This equation is based on augmenting a basic Solow model, very much in accordance with the procedure set forward in Mankiw, Romer and Weil (1992). However, an important difference is that Pritchett does not assume that countries (necessarily) are at their steady state levels of physical and human capital. In the following, the construction of the variables in Pritchett’s model and the data used as basis for them, is further investigated.

\hat{h} Growth of human capital

From the estimates in Barro & Lee (1993) and Nehru, Swanson and Dubey (1995), Pritchett constructs a measure of educational capital from the microeconomic specification of earnings used by Mincer (1974).⁷ He assumes that the natural log of the wage is a linear function of the years of schooling:

$$(5.2) \quad \ln(w_N) = \ln(w_0) + r * N$$

or solved for w_N , showing that wage is subject to exponential growth:

$$(5.3) \quad w_N = w_0 * e^{rN} \quad 8$$

The value of the *stock* of educational capital at any time t is then defined as the discounted value of the wage premium (for all subsequent periods from t to retirement T), due to education:

$$(5.4) \quad HK(t) = \sum_t^T \delta^t * (w_N - w_0)$$

⁷ I will restrict my analysis to using only Barro & Lee’s dataset on educational attainment from Pritchett (1996), as these are the results stated in Pritchett (1996) table 2, column 1, 2 and 3, page 375. It is also stated that using Nehru and others’ (1995) educational dataset yield similar educational capital coefficient estimates.

⁸ This equation is not included in Pritchett (1996) and is stated only to make it easier to follow the evolvement of the equations. We will use this equation’s definition shortly.

Inserting for w_N as defined in (5.3), and moving w_0 outside the summation sign, as it is assumed to be constant⁹:

$$(5.5) \quad HK(t) = w_0 * \sum_t^T \delta^t * (e^{rN} - 1)$$

And taking logs yields

$$(5.6) \quad \ln(HK(t)) = \ln\left(\sum_{t=0}^T \delta^t\right) + \ln(w_0(t)) + \ln(e^{rN} - 1)$$

This is the equation for the log of the stock of educational capital. We are interested in the growth of this measure over time. Pritchett chooses, as with the unskilled wage term (w_0), to treat the discount factor (δ) as fixed over time.¹⁰ Under these assumptions, the two first terms on the right-hand side in equation (5.6); $\ln\left(\sum_{t=0}^T \delta^t\right) + \ln(w_0(t))$, will remain unchanged over time, and the proportional rate of growth of the stock of educational capital is reduced (and approximated) to:

$$(5.7) \quad \dot{hk}(t) \equiv d \ln(\exp^{rN(t)} - 1) / dt$$

This is Pritchett's proxy for \hat{h} , the growth of human capital per worker in equation (5.1).

So what does equation (5.7) yield when numbers are inserted? Let's look at an example using average years of schooling for the adult population aged 25 or older for Australia from Barro & Lee's dataset and an assumed wage increment per year of schooling (r) of 10 percent (as used by Pritchett following Mincer (1974)):

⁹ That the wage of labour with no education is equal to minimum wage and stays constant over time is, at best, a big simplification for at least to reasons; Firstly, most of minimum wage earners have some education (at least within OECD countries). Secondly, the minimum wage does not stay constant over time. This last reason is also acknowledged by Pritchett, but not incorporated into his calculations.

¹⁰ The discount factor depends on the average age of the labour force, as the discount is only until retirement. This varies across countries, but Pritchett assumes that these variations are small over time.

Table 5.1: HC vs log-growth

A	B	C	D	E	F
country	year	B&L avg years	B&L ln-growth	B&L H.C.	B&L HC growth
Australia	1960	8,93		0,3663	
Australia	1965	8,94	0,11 %	0,3680	0,17 %
Australia	1970	10,09	12,10 %	0,5555	18,75 %
Australia	1975	10,01	-0,80 %	0,5429	-1,26 %
Australia	1980	10,08	0,70 %	0,5540	1,10 %
Australia	1985	10,24	1,57 %	0,5790	2,51 %

In column E (B&L H.C.), $\ln(\exp^{RN(t)} - 1)$ is calculated with N being Barro & Lee's average years of schooling (column C), so that the measurement for Australia in 1960 is calculated as follows: $\ln(\exp^{(0,1*8,93)} - 1) = 0,3663$. This number has little or no economic interpretation in itself, however, the subsequent growth of this measurement is an approximation to the growth of the stock of educational capital per worker from period t-1 to t (i.e. from 1960 to 1965). This is shown in column F (B&L HC growth), and is calculated simply by subtracting B&L H.C. in year t-1 (1960) from B&L H.C. in year t (1965).¹¹

Column D (B&L log-growth) shows the logarithmic growth of the average years of schooling in column C, so as to make it comparable to the growth-factors of Pritchett's measure of the stock of educational capital. From this table it seems that using Pritchett's approximation yields somewhat larger growth factors (both positive and negative), and this turns out to hold true for the entire dataset. The two possible proxies to human capital also seem to have a large amount of correlation between them. In fact, when calculating the correlation coefficient¹², it turns out to be 98.98%, which is to be expected as they are based on the same numbers.

\hat{k} - Growth in physical capital

Physical capital is in Pritchett (1996) more accurately referred to as; Cumulated Depreciated Investment Effort (CUDIE) following his discussion on the matter in Pritchett (2000).

Pritchett uses two CUDIE series, one from King and Levine (1994) and one from Nehru and Dhareshwar (1993). The two series are stated as being highly correlated and yielding similar results, so in the following only King & Levine's dataset on growth of physical capital per worker is used. The data is in "1985 international prices" and growth in physical capital is calculated in the following way:

¹¹ It is only an approximation because of a couple of problems addressed earlier; the discount factor and the wage term are both assumed constant.

¹²
$$Correl(D, F) = \frac{\sum (d - \bar{d})(f - \bar{f})}{\sqrt{\sum (d - \bar{d})^2 \sum (f - \bar{f})^2}}$$

$$\hat{k} = \ln(k_t) - \ln(k_{t-1}) \quad (\text{Example for Australia in column D below})$$

Table 5.2: Growth in physical capital per worker

A	B	C	D
country	year	Phys.cap	Phys.cap ln-growth
Australia	1960	19115,30	
Australia	1965	21803,52	13,16 %
Australia	1970	26026,76	17,71 %
Australia	1975	28749,40	9,95 %
Australia	1980	31795,18	10,07 %
Australia	1985	34233,51	7,39 %

\hat{y} - Growth of real GDP per worker

In our regression model, Growth in real gross domestic product per worker (rgdpw) is the dependent variable. Data are from Penn World Tables (PWT) Mark 5 (1988). Since then there has been published new versions of the PWT, but using the same as originally used by Pritchett seems natural. The growth factors are calculated as in the abovementioned case of physical capital;

$$\hat{y} = \ln(y_t) - \ln(y_{t-1}) \quad \text{and stated for Australia in column D below}$$

Table 5.3: Growth in GDP per worker

A	B	C	D
country	year	rgdpw	rgdpw ln-growth
Australia	1960	17753	
Australia	1965	19579	9,79 %
Australia	1970	23313	17,46 %
Australia	1975	24785	6,12 %
Australia	1980	25521	2,93 %
Australia	1985	26855	5,10 %

\hat{a} - Growth rate of the growth-accounting residual (TFP)

Total factor productivity (TFP) enters equation (5.1) as a residual. All growth in output not explained by growth in the two inputs (physical and human capital weighted by their factor shares α_k and α_h), is attributed to this residual, which is thought to include underlying technology growth and increases in efficiency that is not directly attributable to growth in

physical and human capital. As it is difficult to observe directly, one way of measuring the growth rate of TFP is through growth accounting. In the following, when regressing Pritchett's model, TFP does not enter as an explanatory variable, but the effect is still there. So the question is how this will affect the regression results, and where the effect of growth in TFP ends up. In Pritchett's model, since there are no assumptions of differences in underlying growth between countries or in different time periods, one possible interpretation is that TFP will be included in the constant term. However, one should generally take care when interpreting the constant in regressions. The equation from Pritchett's model which will be used in the econometric part of this thesis, thus takes the form:

$$(5.8) \quad \hat{y}_{it} = \Gamma + \alpha_k * \hat{k}_{it} + \alpha_h * \hat{h}_{it} + \varepsilon_{it}$$

Where Γ is the constant term, while the subscript t denotes time and i denotes the country.

5.2 Deriving the regression model of De la Fuente & Doménech (2002)

In De la Fuente & Doménech (2002), the authors have revised and updated their previous versions, and the following is based on this version. More on the article as a whole and its results is to be found in subchapter 3.5.

Notations used by D&D:

Δ	Growth rate for different variables (over sub-period ending at t) ¹³
q_{it}	Log of output per employed worker (in country i at time t)
z	Log of the stock of physical capital per employed worker
h	Log of average years of schooling for adult population (25 and older)
he	Log of average number of years of schooling of employed workers (25 and older)
α	Estimation coefficient for physical capital per employed worker
b	Estimation coefficient for human capital per employed worker
β	Estimation coefficient for human capital per worker
a_{it}	Log of total factor productivity (TFP)
η_t	Fixed time effect
γ_i	Fixed country effect
e_{it}	Log of employment ratio
ε_{it}	Error term

¹³ D&D use t as denotation for sub-period starting at t , but I will change this notation to sub-period ending at t , so as to keep some consistency from preceding chapters.

De la Fuente & Doménech assume that educational attainment (HE) is one of the inputs in a constant-returns Cobb-Douglas aggregate production function. This is meant to explain the dependent variable output, together with physical capital and total factor productivity (TFP), shown in equation (5.9) in intensive form, where all variables are per employed worker:

$$(5.9) \quad q_{it} = a_{it} + \alpha * z_{it} + b * he_{it}$$

De la Fuente & Doménech (D&D) recognizes that when trying to estimate equation (5.9) their estimate of human capital (H), as created, refers to the adult population age 25 and over, and not specifically to employed workers. To correct for this inconsistency they hypothesize that HE (educational attainment for employed workers) increases with population attainment (H) and decreases with the ratio of employment of the adult population (E). The first of these assumptions seems very straight forward, however, that average educational attainment of the work force decreases when employment increases, is not so clear. The relation is not discussed in detail in the article, but it seems reasonable that if unemployment increases from a given level, it is, more often than not, those with less than average education whom are forced into unemployment first. One could construct situations where this relationship seems less viable, but on average it seems reasonable. Employing these assumptions yields:

$$(5.10) \quad he_{it} = c * h_{it} - d * e_{it} \quad (\text{All variables in logarithms})$$

Inserting (5.10) into (5.9) results in the reduced-form production function;

$$(5.11) \quad q_{it} = a_{it} + \alpha z_{it} + \beta h_{it} - \varphi e_{it} \quad , \quad \text{where} \quad (5.12) \quad \beta = bc \quad \text{and} \quad \varphi = bd^{14}$$

This is likely to introduce a bias in the coefficient related to the human capital term, but for now, in accordance with D&D, it is recognized and accepted that β is likely to be a biased estimate of b , which is the parameter D&D are really interested in.¹⁵ Based on equation (5.11), they estimate a number of different specifications, by using different schooling series and also introducing other variables. In the following the focus will be on the equations most

¹⁴ Where c is a coefficient of the impact of growth in human capital per worker on growth in human capital per employed worker, while d is the impact of the employment level on human capital per employed worker.

¹⁵ We will see later on in this paper that this does not create problems.

relevant to this thesis. Equation (5.13) below is derived from (5.11) by replacing a_{it} by a set of period (η_t) and country (γ_i) dummies and introducing an error term (ε_{1it});

$$(5.13) \quad q_{it} = \Gamma_1 + \gamma_i + \eta_{1t} + \alpha z_{it} + \beta h_{it} - \varphi e_{it} + \varepsilon_{1it}$$

Taking differences of (5.13) gives equation (5.14);

$$(5.14) \quad \Delta q_{it} = \Gamma_2 + \eta_{2t} + \alpha \Delta z_{it} + \beta \Delta h_{it} - \varphi \Delta e_{it} + \varepsilon_{2it} \quad 16 \quad 17$$

It turns out that this equation can be simplified even further. When regressing equation (5.13), without country fixed effects, and controlling for the employment ratio, D&D find that φ is highly significant and with the expected negative sign. However, they further state; “*for the remaining equations, e_{it} turned out to be non-significant (which is not surprising given its very small time variation), so this variable is omitted (with very marginal changes in the remaining coefficients)*”.¹⁸ Hence the regressions of the other specifications are done without employment as an explanatory variable. Accepting De la Fuente & Doménech’s argument for excluding employment, equation 5.14 is further simplified to:

$$(5.15) \quad \Delta q_{it} = \Gamma_2 + \eta_{2t} + \alpha \Delta z_{it} + \beta \Delta h_{it} + \varepsilon_{2it}$$

The exclusion of employment as an explanatory variable increases the similarity to the model chosen from Pritchett (1996), and this is therefore the specification that is central in the following, where the differences between the two papers results are analyzed.

¹⁶ The country fixed effects are eliminated as they are fixed over time.

¹⁷ In D&D(2002) there is a typographical error where b_{it} , the technological gap measure is included one equation to early.

This is corrected in their most recent publication De la Fuente & Doménech (2006).

¹⁸ D&D (2002) page 27

5.3 Assessing the differences

So in what way do the models set forward by De la Fuente & Doménech on the one side, and Pritchett on the other, differ? How can their results and conclusions be so radically in disagreement, when they apparently have such similar models?

Both Pritchett and D&D base their models on an augmented Solow-model, and even though the evolvement of the two respective models are based on different reasoning and actions, the two equations that are focused upon (one from D&D and one from Pritchett), seem to be of very equal nature. Restating equation (5.8) from subchapter 5.1 and equation (5.15) from subchapter 5.2:

$$(5.8) \quad \hat{y} = \Gamma + \alpha_k * \hat{k} + \alpha_h * \hat{h} + \varepsilon$$

$$(5.15) \quad \Delta q_{it} = \Gamma_2 + \eta_{2t} + \alpha \Delta z_{it} + \beta \Delta h_{it} + \varepsilon_{2it}$$

Recalling the notations stated at the beginning of the respective subchapters, we see that the equations are very similar, but there are still some notable differences;

- a) The inclusion of time fixed effects (η_{2t}) in D&D's equation (5.15).
- b) The possible distortion of Pritchett using $h\dot{k}(t) \cong d \ln(\exp^{rN(t)} - 1) / dt$ versus D&D using log-growth when constructing their respective proxies for human capital.
- c) The underlying data used to construct the different variables; output, physical and human capital.

So the next step will be to try to isolate and assess the impact these different sources have on the regression results. They will in the following be differentiated and further explained one by one:

- a) The specification of the particular models may in itself be a potential source for the discrepancies observed in the results set forward in the two articles. The effect of including a dummy variable for time specific effects must therefore be investigated further. I will try to

isolate this effect by including a time specific dummy variable in Pritchett's equation (5.8) , effectively transforming the model into D&D's equation (5.15), and evaluate how this alteration affects the results in the model. Keeping everything else as in the original equations, (large) changes in the coefficients would indicate that the specification in itself may, at least in parts, be the source of the observed differences in results.

b) As briefly noted earlier, using Pritchett's proxy for human capital

($h\dot{k}(t) \equiv d \ln(\exp^{r^N(t)} - 1) / dt$) created somewhat larger magnitudes (both positive and negative) than using log-growth directly. In Table 5.4 below shows examples for both B&L's and D&D's data for Australia, where column D shows logarithmic growth, and column F shows human capital growth as constructed according to Pritchett's paper. These observed differences in magnitudes, exemplified here, hold true for all observations of both datasets.

Table 5.4: B&L vs D&D

A	B	C	D	E	F
<u>Barro & Lee</u>					
		B&L avg years	B&L ln-growth	B&L H.C.	B&L HC growth
Australia	1960	8,93		0,3663	
Australia	1965	8,94	0,11 %	0,3680	0,17 %
Australia	1970	10,09	12,10 %	0,5555	18,75 %
Australia	1975	10,01	-0,80 %	0,5429	-1,26 %
Australia	1980	10,08	0,70 %	0,5540	1,10 %
Australia	1985	10,24	1,57 %	0,5790	2,51 %
<u>De la Fuente & Doménech</u>					
		D&D avg years	D&D ln-growth	D&D HC	D&D HC Growth
Australia	1960	9,84		0,5162	
Australia	1965	10,48	6,27 %	0,6161	9,99 %
Australia	1970	11,06	5,42 %	0,7047	8,86 %
Australia	1975	11,72	5,78 %	0,8015	9,68 %
Australia	1980	12,41	5,72 %	0,9000	9,85 %
Australia	1985	12,76	2,77 %	0,9487	4,86 %

But do these differences in magnitude change the estimates of the coefficients in any significant way? To check this, both Pritchett's and D&D's model will be regressed using both proxies for human capital. If the coefficients change significantly (within each model), while holding everything else unchanged, this would indicate that the construction of the human capital variable in itself may be contributing to the differing results.

c) To isolate the effect of the datasets on educational attainment, both datasets will be used keeping the sources for growth in output and physical capital fixed. Testing in both models, and for both calculation methods of the human capital term, will help identify this effect. It may also be so that some of the observed discrepancies in the results are caused by differences in the data on physical capital and/or output. This will also be investigated, but the details of how these datasets are constructed are not examined in detail in this paper.

5.4 Panel data and the econometric procedure

In the models discussed in preceding subchapters, there are have observations stretching over two dimensions, cross-time and cross-country. Two kinds of information are incorporated in such a dataset; the cross-sectional information in the differences between, in our case, countries at the same time, and the time-series information regarding the individual country's changes over time¹⁹. Using panel data regression techniques makes it possible to take advantage of both these types of information at the same time. In our setting, focusing on 21 OECD countries, there are an equal number of observations for each country and for each time period (a balanced panel). When reading Pritchett (1996), it seems as if he concentrates on using Ordinary Least Squares (OLS) throughout his paper, and certainly in the regressions relevant to this thesis, where it is clearly stated. Within the panel data package in PCgive (which is the econometric software package that I have chosen to use), there is a model-specification called “*OLS (pooled regression)*”. A pooled regression, when dealing with panel data, refers to a panel model that has constant coefficients (for both intercepts and slopes). Thus assuming no significant time fixed effects or country fixed effects (as Pritchett does). Our basic econometric panel data equation in Pritchett's model takes the form:

$$(5.16) \quad \hat{y}_{it} = a + \alpha_k * \hat{k}_{it} + \alpha_h * \hat{h}_{it} + \varepsilon_{it}$$

Where the constant term, a , is assumed constant both over time and across countries.

¹⁹ In explanations of basic panel data models it is common to denote the cross sectional (country) dimension as i and time specific dimension as t , where t almost always refers to i.e. a year. It is worth mentioning that in our case t refers to both observations in a singular year (stock), but also, when dealing with growth in a variable from one period to another, t refers to the growth of the preceding 5-year period (flow), i.e.: $\hat{x}_t = \ln(x_t) - \ln(x_{t-5})$

Equation (5.15), taken from De la Fuente & Doménech (2002), relaxes the restriction of Pritchett's model somewhat by allowing for time specific effects. As in Pritchett's model, the slopes are still assumed constant, but now we open for the possibility that intercepts may differ according to time (still assuming no country fixed effects). One way to incorporate this is by simply adding time specific dummy variables (one less than the number of time observations) to the OLS (pooled) estimation used in Pritchett's specification.²⁰ These time dummies ($\omega_1 - \omega_4$) take on value of either zero or one²¹, and the model can be expressed by the following equation:

$$(5.17) \quad \hat{y}_{it} = a + \alpha_k * \hat{k}_{it} + \alpha_h * \hat{h}_{it} + \omega_1 1970 + \omega_2 1975 + \omega_3 1980 + \omega_4 1985 + \varepsilon_{it}$$

Where a is the constant estimated for the observations for 1965, while the constant for i.e. 1970 is calculated by adding up $a + 1970$, where 1970 denotes the estimated coefficient of the dummy variable for 1970.

When using statistical techniques such as ordinary least squares (OLS), a number of assumptions are made. Among others, for OLS to be properly applied, the error terms have to be independent and homoskedastic, meaning that the random variables have the same variance. These conditions are often unrealistic to expect within panel data models. For example, the error term could increase with each observation, something that is often the case both with cross-sectional and time-series, and certainly then with error terms that incorporates both of these aforementioned measurement errors. Thus, it is possible that our data suffer from heteroskedastisity (between countries) and/or autocorrelation (the error terms being correlated over time, i.e. increasing over time). However, since neither Pritchett nor Doménech & De la Fuente discuss or seem to test for these possible distortions, and since our goal is to identify what causes the differences between these two models' findings, this aspect is not focused upon.

²⁰ If $\omega_1, \omega_2, \omega_3, \omega_4$ are all zero, we are left with the time-specific intercept of 1965.

²¹ One if the observation stems from that period, zero if not.

6 Results

This chapter states the results of the different regressions. In total 32 regressions were performed, 16 on Pritchett's (1996) model and 16 on De la Fuente & Doménech's (2002)(D&D) model, where the only difference between the two is the inclusion of time dummies in D&D's model. Most of the results are commented upon, and all the results of the regressions are summed up in the two tables; Table 6.1: OLS Pooled and Table 6.2: OLS Pooled with time specific dummies. All inputs, both dependent and explanatory, are in growth rates, and thus the estimated coefficients can be seen as estimates of how much a percentage growth in the variable affects growth in output. Using a 95% confidence interval, a coefficient is deemed significantly different than zero if the corresponding t-value is larger than 2.²² T-statistics are given in parentheses'.

6.1 Results within Pritchett's model

In Table 6.1: OLS Pooled, the results of the different estimations of Pritchett's model are shown. Column 1-8 shows regression results when using GDP per worker from Penn World Tables Mark 5 (1988) as dependent variable, while column 9-16 shows regressions with GDP per worker from Dabán, Doménech & Molinas (1997) as dependent variable.

Column 1 shows Pritchett's original specification; data for physical capital per worker from King & Levine (1994)(K&L), human capital from Barro & Lee (1993)(B&L) and Pritchett's own calculation method for the proxy of human capital growth, HC. The results are similar to what we would expect after reading Pritchett (1996).²³ The estimated impact of growth in human capital, α_h , enters with a negative sign (-0.035) and insignificantly (t=0.71). The estimated coefficient for physical capital, α_k , is 0.769 (higher than all of Pritchett's findings) and highly significant (t=12.30), and R^2 , the "fit" of the model, is calculated to 0.664.²⁴

²² T-statistics refers to Student's t-test, and using a confidence interval of 95%, and with null hypotheses being that the estimated coefficient is equal to zero, we can (with approximately 100 degrees of freedom (observations minus explanatory variables)) reject the null hypotheses if the t-statistic is higher than 1.984, or roughly 2.

²³ But not directly comparable as we are focusing on 21 OECD countries, while Pritchett focuses on larger samples.

²⁴ In our linear model, R^2 is the square of a correlation coefficient, which can be calculated as $R^2=1-(RSS/TSS)$ where RSS= residual sum of squares and TSS= total sum of squares, for more on this see i.e. Johnston and DiNardo (1997) or Greene (2003)

In column 2, Dabán, Doménech & Molinas (1997)(DD&M) is used as source for growth of physical capital per worker, reducing α_k to 0.565 (t=13.2), α_h stays slightly negative, while R^2 reduces to 0.490. Column 3 and 4 repeat 1 and 2 respectively, with “log-growth” (of average years of schooling) replacing HC as human capital proxy. This does not alter the results much.

Columns 5-8 correspond to reproducing 1-4 using human capital data from D&D (2002). Somewhat unexpectedly, this leads to more negative estimates on the impact of human capital on output, for all 4 specifications. The impact is largest when using physical capital from DD&M (comparing column 2 with 6, and 4 with 8). In column 8 we see that compared to column 4, using D&D’s dataset on average years of schooling decreases α_h from -0.027 to -0.536, though still not significantly different from zero.

The impact of changing the data source for the explained variable (growth in output per worker - \hat{y}), from Penn World Tables Mark 5 (PWT) to DD&M, can be seen by comparing columns 1-8 with 9-16 respectively.²⁵ Using DD&M’s estimates on growth in output per worker yields positive α_h ’s throughout, though statistically significant only for the specification in column 15. When using PWT, α_h was consistently estimated to be negative. At the same time, α_k is lower in columns 9-16 than in 1-8 when corresponding specifications are compared (1 versus 9, 2 versus 10 etc). R^2 is slightly lower for the specifications where physical capital from K&L is used to explain output from DD&M, than when the same specification is used to explain output per worker from PWT. On the other hand, changing data on physical capital per worker to DD&M, seems to yield opposite results; increased R^2 when output from DD&M is being explained.

Of all 16 regressions of Pritchett’s model, the estimated coefficient of the human capital term, α_h , enters significantly only once, in column 15. In this specification, data on growth in output per worker from DD&M is explained by human capital data from D&D calculated as log growth, and physical capital data from K&L. The estimated fit of this specification measured by R^2 is 0.656.

²⁵ DD&M replicates the Penn World Table for the OECD-countries using national accounts data from the OECD, and a set of purchasing power parities specific to this sample. Data and guidance on how these were used was obtained directly from Professor Rafael Doménech.

Table 6.1: OLS Pooled

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
GPD per worker	Penn World Tables (Mark 5) (1988)								Dabán, Domenéch & Molinas (1997)							
Human capital data	B&L (1993)				D&D (2002)				B&L (1993)				D&D (2002)			
Human capital calculation method	HC		Log-growth		HC		Log-growth		HC		Log-growth		HC		Log-growth	
Physical capital data from	K&L	DD&M	K&L	DD&M	K&L	DD&M	K&L	DD&M	K&L	DD&M	K&L	DD&M	K&L	DD&M	K&L	DD&M
α_h	-0.035 (0.71)	-0.016 (0.32)	-0.045 (0.72)	-0.027 (0.42)	-0.183 (0.61)	-0.470 (1.07)	-0.105 (0.25)	-0.536 (0.83)	0.018 (0.59)	0.036 (1.22)	0.032 (0.78)	0.045 (1.20)	0.343 (1.50)	0.074 (0.31)	0.725 (2.39)	0.265 (0.82)
α_k	0.769 (12.3)	0.565 (13.2)	0.770 (12.3)	0.566 (13.2)	0.768 (13.0)	0.571 (13.5)	0.770 (12.3)	0.578 (12.4)	0.642 (15.7)	0.561 (13.4)	0.642 (15.6)	0.559 (13.4)	0.645 (16.0)	0.559 (13.0)	0.635 (16.6)	0.554 (12.5)
Constant	-0.016 (1.19)	0.005 (0.44)	-0.016 (1.23)	0.005 (0.458)	-0.006 (0.30)	0.033 (1.21)	-0.014 (0.77)	0.024 (0.99)	0.025 (2.45)	0.022 (2.34)	0.025 (2.41)	0.023 (2.42)	0.004 (0.20)	0.021 (1.13)	-0.003 (0.22)	0.0154 (0.99)
R ²	0.664	0.490	0.664	0.491	0.664	0.500	0.662	0.497	0.639	0.664	0.642	0.664	0.646	0.661	0.656	0.663
R ² adj	0.657	0.480	0.657	0.481	0.657	0.490	0.655	0.487	0.632	0.657	0.635	0.657	0.639	0.654	0.649	0.656

6.2 Results within De la Fuente & Doménech's model

Table 6.2: OLS Pooled with time specific dummies, shows the results of estimating Doménech & De la Fuente's model. Column I-VIII shows regression results when using GDP per worker from Penn World Tables Mark 5 (1988) as dependent variable, while column IX-XVI shows regressions with GDP per worker from Dabán, Doménech & Molinas (1997) as dependent variable. In D&D's model, allowing for the possibility of the constant to vary over time (but not between countries), by including time dummy variables, yields different estimated values of this term for the different time-periods. In Table 6.2 the estimated value of the constant refers to the estimated value for 1965 (or specifically for the growth in the preceding five-year period). The values of the respective dummy coefficients (for 1970, 1975, 1980 and 1985) are the estimated difference in the constant compared to 1965 which serves as a "benchmark". To calculate the constant for i.e. 1970, the coefficient of the dummy for 1970 should be added to the constant term.

In column I, the results of using Pritchett's proxy for growth in human capital (HC), calculated on the basis of B&L's dataset and incorporated into D&D's model, are shown. The estimated coefficient of the growth of human capital per worker, α_h , is close to zero (-0.002), and insignificant (t=0.04). Growth in physical capital per worker is estimated to 0.696 and is highly significant (t=12.00). Altering the proxy for human capital growth to logarithmic growth in the average years of schooling, while keeping everything else as above, leads to only minimal changes, and can be seen in column III. In columns II and IV, where we have altered the source of physical capital to DD&M, α_h is still close to zero. α_k shrinks to 0.446 (from 0.696 and 0.697 respectively). R^2 is 0.751 in I and III and lowered to 0.647 in II and IV.

In column V, HC is used as proxy, now calculated from schooling data from D&D's dataset. This alters the coefficient of the human capital term to 0.135, but still not significant (t=0.53). In column VII, HC is replaced by log growth of average years of schooling as proxy for human capital growth. The estimated impact of growth in human capital on growth in output is 0.289, the highest we obtain when trying to explain growth in output per worker based on PWT-data, but still inhibits a far to low level of significance (t=0.82). The numerically larger

effect of replacing HC with log growth could indicate a higher degree of sensitivity to alterations when using D&D's data on human capital than when using B&L's dataset. The estimated coefficient for physical capital in VII is 0.688 ($t=11.30$) and R^2 is 0.753, the highest with PWT as source for the dependent variable.

Columns IX through XVI shows the results when growth in output per worker is based on data from DD&M, as used by D&D. By changing the dependent variable, the estimated coefficient for growth in human capital per worker, α_h , now enters significantly in seven out of eight specifications, (lowest t-value 1.95 is significant at a slightly lower level than 95%), while when regressing on PWT-data, α_h was never significantly different from zero (highest t-value 0.82). This is indeed a very interesting result. In columns IX to XII, where B&L's schooling data is used, the α_h 's are very modest, ranging from 0.063 to 0.086, while when replacing B&L's data with D&D's, this alters these estimates substantially, with α_h 's now ranging from 0.378 to 1.045!

Column XVI, which replicates D&D's original model explaining output per worker from DD&M, with human capital from D&D measured by log-growth and physical capital from DD&M, yields an estimated coefficient of the impact of growth in human capital of 0.667 ($t=2.58$). α_k , the estimated impact of physical capital is 0.482 ($t=11.40$) and R^2 is calculated to 0.739.

Table 6.2: OLS Pooled with time specific dummies

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI
GPD per worker	Penn World Tables (Mark 5) (1988)								Dabán, Domenéch & Molinas (1997)							
Human capital data	B&L (1993)				D&D (2002)				B&L (1993)				D&D (2002)			
Human capital calculation method	HC		Log-growth		HC		Log-growth		HC		Log-growth		HC		Log-growth	
Physical capital data from	K&L	DD&M	K&L	DD&M	K&L	DD&M	K&L	DD&M	K&L	DD&M	K&L	DD&M	K&L	DD&M	K&L	DD&M
α_h	-0.002 (0.04)	0.007 (0.20)	-0.004 (0.07)	0.006 (0.12)	0.135 (0.53)	-0.028 (0.08)	0.289 (0.82)	0.049 (0.10)	0.063 (2.38)	0.069 (2.82)	0.083 (2.25)	0.086 (2.61)	0.602 (3.09)	0.378 (1.95)	1.045 (4.10)	0.667 (2.58)
α_k	0.696 (12.00)	0.446 (8.91)	0.697 (12.00)	0.446 (8.94)	0.694 (11.70)	0.447 (9.14)	0.688 (11.30)	0.444 (8.79)	0.627 (11.3)	0.501 (11.90)	0.624 (11.3)	0.504 (11.90)	0.619 (11.4)	0.496 (11.50)	0.600 (12.2)	0.482 (11.40)
Constant	0.041 (2.76)	0.092 (4.63)	0.041 (2.80)	0.092 (4.69)	0.034 (1.38)	0.093 (2.86)	0.032 (1.44)	0.091 (2.99)	0.052 (3.00)	0.067 (4.77)	0.053 (3.05)	0.068 (4.86)	0.021 (0.90)	0.050 (2.48)	0.020 (0.96)	0.050 (2.71)
1970	-0.024 (1.75)	-0.022 (1.31)	-0.024 (1.75)	-0.022 (1.31)	-0.024 (1.72)	-0.022 (1.31)	-0.024 (1.69)	-0.022 (1.29)	-0.013 (1.01)	-0.011 (0.76)	-0.013 (0.98)	-0.011 (0.73)	-0.011 (0.83)	-0.009 (0.63)	-0.010 (0.78)	-0.009 (0.60)
1975	-0.095 (9.58)	-0.104 (8.34)	-0.095 (9.58)	-0.104 (8.29)	-0.098 (10.5)	-0.103 (9.59)	-0.098 (10.4)	-0.104 (9.54)	-0.065 (5.67)	-0.069 (6.78)	-0.065 (5.69)	-0.069 (6.73)	-0.069 (5.69)	-0.069 (6.33)	-0.069 (5.67)	-0.070 (6.29)
1980	-0.046 (3.01)	-0.065 (2.77)	-0.046 (2.99)	-0.065 (2.75)	-0.048 (3.37)	-0.064 (3.11)	-0.049 (3.41)	-0.065 (3.20)	-0.046 (4.10)	-0.049 (3.64)	-0.046 (4.05)	-0.048 (3.59)	-0.047 (3.75)	-0.047 (3.45)	-0.049 (3.89)	-0.049 (3.59)
1985	-0.061 (3.23)	-0.115 (4.25)	-0.061 (3.25)	-0.115 (4.27)	-0.063 (3.52)	-0.115 (4.68)	-0.063 (3.53)	-0.115 (4.67)	-0.014 (0.82)	-0.046 (3.30)	-0.015 (0.85)	-0.047 (3.32)	-0.020 (1.19)	0.051 (3.70)	-0.022 (1.30)	-0.052 (3.71)
R ²	0.751	0.647	0.751	0.647	0.752	0.647	0.753	0.647	0.705	0.736	0.706	0.736	0.718	0.733	0.732	0.739
R ² adj	0.736	0.625	0.736	0.625	0.737	0.625	0.738	0.625	0.687	0.720	0.688	0.720	0.701	0.717	0.716	0.723

When comparing the results in column XVI of Table 6.2 (above), which show the results of replicating D&D's original model, to those set forward in D&D(2002)²⁶, they differ somewhat, but not terribly much. The most likely reason for the differences is that D&D expand their data to also include the period 1985-1990, thus increasing the number of observations to 126. Column XII in Table 6.2 corresponds to D&D's regression using D&D's model with Barro & Lee's (1993) data on average years of schooling.²⁷ When comparing, these results are even closer matched. The similarities can be seen in Table 6.3: Comparing with D&D's findings", where the two results from D&D's paper are restated (they do not mention their findings for constants/time dummies), together with the results obtained when trying to replicate these regressions.

Table 6.3: Comparing with D&D's findings

	[c3]	XII	[c8]	XVI
Human capital data	B&L (1993)	D&D (2002)		
α_h	0.089 (2.52)	0.086 (2.61)	0.744 (3.10)	0.667 (2.58)
α_k	0.501 (9.79)	0.504 (11.90)	0.470 (9.34)	0.482 (11.40)
R ²		0.736		0.739
R ² adj	0.722	0.720	0.726	0.723
No of observ.	105	105	126	105

6.3 The models compared

When evaluating the results of regressing Pritchett's model (Table 6.1), against the results of regressing De la Fuente & Doménech's model (Table 6.2), there are some interesting regularities. Including time specific dummy variables increases the estimated coefficient for the human capital term (α_h), while it at the same time decreases the estimated coefficient for the physical capital term (α_k). This holds true for all the regressions when compared with the

²⁶ D&D(2002), Page 28 - table 9c "Growth rates" column [c8] "D&D02"

²⁷ D&D(2002), Page 28 - table 9c "Growth rates" column [c3] "B&L93"

matching specification (with/without time dummies and holding everything else fixed). We also observe that the “fit” of the model, adjusted for the number of explanatory variables, R^2_{adj} ²⁸, is consistently higher when time specific dummy variables are included, comparing corresponding results (1 with I, 2 with II and so on). It should be noted that this is only a crude measure of the models suitability, and with so few observations (especially over time with only five growth periods), one should be careful when making conclusions. Still it gives us some idea of how well the models regression lines approximate the real data points.

By allowing the constant term to vary over time we are able to increase the amount of GDP per worker explained, measured by R^2_{adj} , for all regressions. Together with the observation that many of the dummies enter with significant t-values (true for all estimated dummy coefficients for 1975 and 1980, and most of the coefficients for 1985), this may lead us to believe that there are significant time effects within our dataset.

²⁸ $R^2_{adjusted} = 1 - (1 - R^2) \frac{(n-1)}{(n-p-1)}$

p = number of explanatory variables excluding the constant term (2 in Pritchett’s model and 6 in D&D’s model)
 n = number of observations, which in our case is $(21*5)= 105$

7 Discussions & Conclusions

In this chapter I will discuss the results set forward in chapter 6, and try to identify the possible sources for the disparities found. I will also compare the findings to the original results of Pritchett (1996) and Doménech & De la Fuente (2002) and discuss possible weaknesses with the econometric procedures used.

7.1 Datasets on human capital

The construction of Barro & Lee's (1993) dataset on educational attainment, which Pritchett uses as basis for his proxy on human capital growth, has, as the authors themselves acknowledge, many shortcomings, and substantial measurement error is highly likely. This is mainly caused by unobservable data. The extensive use of backward and forward projections, and usage of regional means to fill in gaps where data is missing, inevitably causes inaccuracies. However, the key weakness of B&L's 1993 dataset, when applied to our context of growth and not levels, seems to be the failure to adjust for changes in classification criteria. They base their data on the duration of the respective schooling levels on UNESCO's statistical yearbook in 1965, and thus correct for differences between countries, but neglect possible variations over time. This may cause serious deficiencies when applied in growth economics. Even the data on OECD countries (which one would expect to be more accurate) are filled with implausible breaks and jumps in the time series that can only be caused by changes in measurement. Some examples of such implausible leaps in B&L's dataset:

- Norway 1970-1975, average years of schooling is reported to have increased from 6.76 years in 1970 to 10.19 years in 1975. De la Fuente & Doménech for the same years, report 10.07 and 10.29.²⁹
- Switzerland 1975-1980, B&L reports a jump from 6.26 to 9.67. D&D calculate 11.39 and 11.63
- Portugal 1965-1970, B&L state that in 1965 average years of schooling in Portugal is 1.78, five years later it has dropped to 1.21. D&D's corresponding numbers are 4.62 and 4.87

²⁹ Pritchett excludes Norway from his analysis based on the argument that this jump/break is impossible. He does not mention any of the other examples mentioned here. I have included Norway in all my regressions, as does D&D.

The negative growth in average years of schooling in Portugal from 1965 to 1970 is one of several reported downswings in educational attainment in Barro and Lee's dataset. In fact, it turns out that when calculating five-yearly growth rates of average years of schooling for the 21 OECD countries used in this paper, 15 out of 105 observed growth rates (14%) are negative. This seems highly unlikely. D&D's dataset seems to contain more plausible values. Nonetheless, also they acknowledge that substantial measurement errors are still possible. The usage of a larger number of sources has still helped to identify where classification criteria's has been changed, making it possible to correct for this, and as a consequence of this, the growth rates should be considerably closer to the true evolvement of average years of schooling. D&D report no negative five-yearly growth in average years of schooling, and the correlation between the growth factors of the two datasets is as low as 9.52%.

Despite the substantial differences in these datasets, when using data on output from PWT and physical capital data from K&L, the change of human capital data from B&L to D&D, (using HC) within Pritchett's model causes more negative estimated coefficients. In D&D's model the estimated impact of human capital is estimated to 0.135, and far from being significant ($t=0.53$). This is not what we would expect when observing De la Fuente & Doménech's results (2002 and 2006). Something else is obviously contributing to the discrepancies between the respective authors' findings.

7.2 Calculating the proxies for human capital

Changing from Pritchett's (1996) proxy for human capital, HC, to log-growth of average years of schooling as used in Doménech & De la Fuente (2002), causes some alterations in the estimated coefficients for human capital growth, α_h , in both models. Within both models the impact of changing the calculation method is higher when D&D's data on human capital is used. This signals that D&D's dataset possibly has a lower level of robustness to alterations in the computation of the human capital proxy. This is most likely a consequence of the much lower fluctuations in growth rates when compared to the dataset of Barro & Lee (1993), as illustrated by the examples in the preceding subchapter. In chapter 5.1 we saw that the correlation between HC and lo-growth for B&L's dataset was 98.98%. The corresponding coefficient for D&D's dataset is 97.12%, still very high. It is therefore quite surprising that altering the proxy calculation method has relatively large consequences, especially for the

estimated coefficients of the impact of growth in human capital. This observation does not suggest that using data from B&L is in any way better than using D&D's data, which seems to be much closer to the actual evolvement of educational attainment. It only points out that small changes in the way the proxy is calculated may cause larger alterations in the results when D&D's dataset is used.

When trying to explain growth in PWT-output, the alteration from HC to log-growth as calculation method for the human capital proxy, increases α_h to 0.289 within D&D's model, but still not significant ($t=0.289$), and far away from the results reported by De la Fuente & Doménech. So altering the model (including/excluding time dummy variables), the dataset for human capital and the way the proxy for human capital is calculated, does not result in a significant human capital coefficient when data on output from PWT is used.

7.3 The impact of other variables

Altering the source of physical capital from King & Levine (1994) to Dabán, Doménech & Molinas (1997), also causes changes in the results. When combined with output data from PWT, the results on the estimated coefficient for human capital is a slight increase when used together with human capital data from B&L, and a larger decrease when combined with human capital data from D&D. This holds true for both models, though the α_h 's are not significantly different from zero for any of these regressions. In fact, when using growth in output per worker from PWT as dependent variable, α_h never enters significantly in any of these regressions (1-8 in table 6.1. and I-VIII in table 6.2.) The correlation between the two growth rates of the two datasets is calculated to 95.34%.

Changing the dependent variable from Penn World tables mark 5 (1988) to Dabán, Doménech and Molinas 1997), causes some larger changes in the estimated coefficients. The correlation between the growth rates of the different datasets is 88.18%. The estimated impact of human capital, the α_h 's, are consistently estimated to be higher than corresponding estimates with data on the growth of output per worker from PWT. This holds true for both models. The α_h 's are significant and positive in all of the regressions where time dummy variables are included, and also positive in Pritchett's model, though only significant in one out of eight

regressions (table 6.1. column 15). At the same time, regressing with DD&M's data on output as dependent variable, leads to lower α_k 's in Pritchett's model, while in D&D's model the α_k 's are lowered when physical capital from K&L is used, and heightened if DD&M's physical capital data is used.

7.4 The models compared/cumulative effects

So what causes the differences in the results set forward by Pritchett on the one side, and Doménech & De la Fuente on the other? It is not solely the difference in human capital data, or the difference in the calculation of the proxy for human capital. Nor can including time dummy variables or changes in the other inputs; physical capital and output data, alone explain the differences. The answer is that it is the cumulated effect of all these differences that leads to their contradicting results. When comparing the two models, we find that seemingly small differences in physical capital, and especially data on growth in output per worker, have large effects on our results. If i.e. D&D used output data from Penn World Tables, Mark 5 (1988), as used by Pritchett, their results, keeping everything else as in their original model, would have been an estimated coefficient of the impact of human capital of 0.049 and not statistically significant from zero ($t=0.10$). This is far from their reported findings (using output data from Dabán, Doménech and Molinas (1997)) of an estimated impact of human capital of 0.744 ($t=3.10$), or in our replicate of this model of 0.667 ($t=2.58$). Even such a seemingly small alteration as changing the calculation method for the growth in human capital, where the correlation between the two proxies is as high as 98.98% (B&L) and 97.12% (D&D), can in some circumstances cause large fluctuations. One interesting observation is that if D&D had used Pritchett's proxy for human capital³⁰, their findings on the impact of growth in human capital on growth in output would have been lowered from 0.667 to 0.378. This illustrates the fragility of the findings. Within the 32 regressions performed in this thesis, the impact of human capital on output per worker ranges from -0.536 ($t=0.83$) to 1.045 (4.10)!

The only finding that is reasonable stable throughout, is the impact of physical capital, ranging from 0.770 ($t=12.30$) to 0.444 ($t=8.79$).

³⁰ Pritchett's proxy for human capital growth was motivated by the wish to link the macro model to microeconomic findings on the monetary return to education (increased wages) following Mincer (1974).

7.5 Possible weaknesses and further research

The comparative analysis conducted in this paper is based on data for 21 OECD countries in five different five-yearly growth periods, summing up to 105 observations. Especially the limitation to only five time observations is a very small sample. This may be one of the reasons for the lack of robustness of the results for the impact of human capital on output. Ideally this time-series should be expanded, and for further study, data on educational attainment, of high quality, should be gathered for the periods up until the present.³¹ The limited time series also restricts the possible choices of econometric model. Within panel data econometrics, there exist many possibilities regarding the choice of model. Ordinary least squares (OLS), as used here, may not be the optimal choice, especially if heteroskedasticity and/or autocorrelation is present in the data. These possible problems are not tested for in this thesis. This should be explored further, and if evidence of such problems is found, the econometric approach should be adjusted accordingly. Another shortcoming of this paper is that the datasets on output (PWT and DD&M) and physical capital (K&L and DD&M) have not been explored.

It would also be interesting to investigate larger cross country samples of such high quality data as D&D's dataset seem to exist of. Gathering such data would however be a formidable task.

This thesis is first and foremost a comparative analysis of contradicting findings on the value of growth in human capital for the growth in output. And while keeping this focus, many interesting subjects are left unexplored. Examples of this are De la Fuente & Doménech's inclusion of a technological gap measure, and combining growth with initial levels, as done by Pritchett. The choice of equations used in this thesis is based on similarity and comparability across models, while at the same time yielding disagreeing results. These equations are not necessarily the ones the respective authors consider most fitting.

³¹ In the case of Doménech and De la Fuente's (2002) dataset, observations for 1990, and also 1995 (for three fourths of the countries) already exist, but these have been left out of this thesis for comparative purposes.

7.6 Conclusions

This thesis investigates what causes the contradictory conclusions of Pritchett (1996) and De la Fuente & Doménech (2002 and 2006) on the role played by growth in human capital in explaining growth in output. It examines the differences in the educational datasets composed by Barro & Lee (1993), used by Pritchett, and De la Fuente & Doménech (2002) for 21 OECD countries using five-year growth periods from 1960 to 1985, and finds that there are large disparities in both levels and growth rates between the datasets. Barro & Lee's data is found to contain implausible jumps and breaks, and over 14% of the growth rates are reported to be negative. This seems highly questionable. De la Fuente & Doménech's dataset projects much smoother growth in educational attainment, and reports no periods of negative growth. However, these differences are not sufficient to explain the contradicting results. Through regressions on several different variations of both models, other important factors contributing to the disparities are identified:

- Differences in the datasets on output per worker
- Differences in the datasets on physical capital per worker
- Excluding/including time fixed effects in the model
- The calculation method for the proxy on human capital

It is through the cumulative effect of all these dissimilarities that the opposing views on human capital are based. By altering these inputs, one may construct models such that the estimated impact of growth in human capital per worker on growth in output per worker may vary from extreme values of -0.536 to 1.045 (the former not being significantly different from zero). The estimated coefficients on growth in human capital are also highly sensitive to seemingly small alterations in the model or any of its inputs, and this lack of robustness should result in taking caution when interpreting results. One possible reason for this high degree of sensitivity is the low number of observations, especially over time (5 growth periods). Quite contradictory though, the estimated impact of growth in physical capital per worker is fairly stable, ranging from 0.444 to 0.770, and highly significant throughout all 32 regressions.

By allowing the constant term to vary over time by including time dummy variables, the estimated impact of human capital increased throughout the regressions. The R^2_{adj} , the

measure of the fit of the model, also increased for all variations. Together with the finding of significant t-values for most of the dummies, this suggests that there seems to be considerable time specific effects within the data, and that De la Fuente & Doménech's inclusion of such dummy variables seems justified.

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